On some continuous-time modeling and estimation problems for control and communication

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Faculty of Health, Science and Technology

Physics

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"*Never Give In, Never, Never, Never*"
Winston Churchill

Abstract

The scope of the thesis is to estimate the parameters of continuous-time models used within control and communication from sampled data with high accuracy and in a computationally efficient way. In the thesis, continuous-time models of systems controlled in a networked environment, errors-in-variables systems, stochastic closed-loop systems, and wireless channels are considered. The parameters of a transfer function based model for the process in a networked control system are estimated by a covariance function based approach relying upon the second order statistical properties of input and output signals. Some other approaches for estimating the parameters of continuous-time models for processes in networked environments are also considered. The multiple input multiple output errors-in-variables problem is solved by means of a covariance matching algorithm. An analysis of a covariance matching method for single input single output errors-in-variables system identification is also presented. The parameters of continuous-time autoregressive exogenous models are estimated from closed-loop filtered data, where the controllers in the closed-loop are of proportional and proportional integral type, and where the closed-loop also contains a time-delay. A stochastic differential equation is derived for Jakes's wireless channel model, describing the dynamics of a scattered electric field with the moving receiver incorporating a Doppler shift.

For Sadia, Marium and Anaya

List of contributions

The thesis is on continuous-time parameter estimation and its applications within control and communication. The contributions are given on networked control system identification, errors-in-variables system identification, wireless channel modeling and stochastic closed-loop system identification. The thesis consists of five main parts, where the first part is an introduction.

Part I - Introduction

Part II - Networked Control Systems

1. Y. Irshad, M. Mossberg and T. Söderström. *System identification in a networked environment using second order statistical properties*.

   A version without all appendices is published as
   Y. Irshad, M. Mossberg and T. Söderström. *System identification in a networked environment using second order statistical properties*. Automatica, 49(2), pages 652–659, 2013.

   Some preliminary results are also published as
   M. Mossberg, Y. Irshad and T. Söderström. *A covariance function based approach to networked system identification*. In Proc. 2nd IFAC Workshop on Distributed Estimation and Control in Networked Systems, pages 127–132, Annecy, France, September 13–14, 2010.

2. Y. Irshad and M. Mossberg. *Some parameters estimation methods applied to networked control systems*.

   A journal submission is made.

   Some preliminary results are published as
   Y. Irshad and M. Mossberg. *A comparison of estimation concepts applied to networked control systems*. In Proc. 19th Int. Conf. on Systems, Signals and Image Processing, pages 120–123, Vienna, Austria, April 11–13, 2012.

Part III - Errors-in-variables Identification

3. Y. Irshad and M. Mossberg. *Continuous-time covariance matching for MIMO EIV system identification*.

   A journal submission is made.

4. T. Söderström, Y. Irshad, M. Mossberg and W. X. Zheng. *On the accuracy of a covariance matching method for continuous-time EIV identification*.

   Provisionally accepted for publication in Automatica.

Some preliminary results are published as
T. Söderström, Y. Irshad, M. Mossberg, and W. X. Zheng. *Accuracy analysis of a covariance matching method for continuous-time errors-in-variables system identification*. In Proc. 16th IFAC Symp. System Identification, pages 1383–1388, Brussels, Belgium, July 11–13, 2012.

Part IV - Wireless Channel Modeling

5. Y. Irshad and M. Mossberg. *Wireless channel modeling based on stochastic differential equations*.

   Some results are published as
   M. Mossberg and Y. Irshad. *A stochastic differential equation for wireless channels based on Jakes's model with time-varying phases*, In Proc. 13th IEEE Digital Signal Processing Workshop, pages 602–605, Marco Island, FL, January 4–7, 2009.

Part V - Closed-loop Identification

6. Y. Irshad and M. Mossberg. *Closed-loop identification of P- and PI-controlled time-delayed stochastic systems*.

   Some results are published as
   M. Mossberg and Y. Irshad. *Closed-loop identification of stochastic models from filtered data*, In Proc. IEEE Multi-conference on Systems and Control, San Antonio, TX, September 3–5, 2008.

My contribution is as follows:

Part - II

1. I carried out some parts of the written work. My major contribution was in the form of the simulations and the analysis.
2. I carried out the majority of the written work, the simulations and the analysis.

Part - III

3. I carried out the majority of the written work, the simulations and the analysis.
4. I carried out the simulation work and some of the analysis. Some parts of the written works is made by me.

Part - IV

5. I carried out the majority of the written work along with the modeling and the simulations. Some parts of the analysis are made by me.

Part - V

6. I carried out the majority of the written work, the simulations and some of the analysis.

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Contents

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Part I

Introduction

i System identification and parameter estimation

System identification is about finding mathematical models of systems that are intended for a certain purpose such as control and communication. Within system identification, discrete-time models are most common, although the natural description of physical systems existing in physical world is in terms of continuous-time models. Continuous-time models give natural mathematical descriptions of physical systems. Examples of mathematical models of the physical systems in continuous-time exist in almost all fields of science and technology. The mathematical models help to explain the physical systems, to predict their behaviors, to gain a better understanding of the functions of physical systems.

The thesis is on parameter estimation in continuous-time stochastic models used within control and communication. The thesis consist of five parts along with six contributions. Part I of thesis, is an introduction to the subject. Part II of the thesis, with contribution 1 and 2, is on the application of estimation theory to the field of networked control systems. In contribution 1, identification of system in the networked environment is considered by a covariance function based method that relies on the second order statistical properties of the output signals. In contribution 2, some estimation concepts are applied to networked control systems. Part III of the thesis, with contribution 3 and 4, is on continuous-time errors-in-variables identification . In contribution 3, the continuous-time multiple input multiple output errors-in-variables systems identification problem is solved by means of covariance matching and in contribution 4, an analysis of a covariance matching method for continuous-time errors-in-variables system identification is made. Part IV of the thesis, with contribution 5, is on the application of continuous-time modeling to the field of wireless channel, in which a wireless channel is modeled based on stochastic differential equations. Part V of the thesis, with contribution 6, is on closed-loop system identification, in which parameter estimation is made for a system in a time-delayed stochastic closed-loop which is controlled by proportional (P) and proportional integral (PI) controller.

This part of the thesis is an introduction to parameter estimation in continuous-time descriptions along with an introduction to network control systems, errors-in-variables systems, wireless channel modeling, and closed-loop identification. Finally, this part also has an outline of the six contributions.

i.i Continuous-time parameter estimation

The thesis is about estimation of parameters in continuous-time models used within control and communication. In parameter estimation, algorithms are proposed and mathematical models of the systems are fitted to the available discrete-time data corrupted by stochastic disturbances. A description of parameter estimation is given by block diagram presented in Figure 1. In parameter estimation, the physical systems are described in terms of appropriate mathematical models with unknown parameter and the parameter of mathematical models are estimated from discrete-time data in the form of input and output signals by simulating proposed algorithms. The proposed algorithms are analyzed under rigorous simulation by changing different parameter within proposed algorithms and by changing different parameter of the physical system and results are presented. The continuous-time models of networked control systems, errors-in-variables systems, wireless channel modeling, and closed-loop stochastic system are considered in this work.

i.ii Historical background

The field of system identification has grown in size and diversity over several decades and is now a matured field. Åström and Eykhoff in [1] presented a survey mainly focused on system identification in discrete-time. A first significant development in the field of continuous-time system identification is a survey report by Young in [2], which is a review on the progress of research on parameter estimation of dynamic systems in continuous-time. Subsequently, rapid developments were made in this subject, which is described in a survey on continuous-time system identification by Unbehauen and Rao in [3]. Furthermore, several books [4–6] and publications [7–10, 10–18] are found on the subject, which is widely discussed in the recent proceedings [2,19–22].

The field of system identification has been largely on discrete-time models for the description of dynamic systems as input and output signals are observed in discrete-time. The description of dynamic systems in continuous-time has several advantages over the description of dynamic systems in discrete-time. The continuous-time descriptions of the dynamic systems is a natural basis of our understanding because all basic physical laws are in continuous-time and they provide a good description of the dynamic systems. In the digital age stretched over nearly more than half century, higher sampling rates is one of the emerging requirements. Discrete-time descriptions of dynamic models at higher sampling rates is not desirable. The discretization of continuous-time descriptions to discrete-time descriptions at higher sampling rates cluster the poles of the discrete-time descriptions close to unity, which is an undesirable situation as it gives rise to sensitivity problems.

Two natural approaches for identification of continuous-time systems are the indirect approach and the direct approach [10,11,23].

- *The indirect approach* in which identification of the parameters is made in discrete-time and a transformation of parameter is made to the continuous-time [24]. The discrete-time parameters has a linear relation with the discrete-time regularly sampled models and are easy to estimate by using standard technique. On the other hand identification of the parameters from the irregularly sampled models are obviously not appropriate by the indirect approach as the discrete-time models are time-varying.

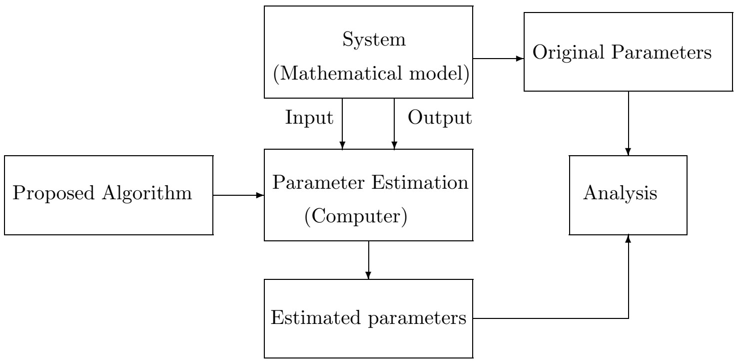

Figure 1: Description of a parameter estimation by block diagram in a computer based simulation scenario. The system parameters are described by an appropriate mathematical models with unknown parameters. Data from the system in the form of discrete-time samples are collected for the parameter estimation. Algorithms are proposed for the estimation of parameter and simulated for available discrete-time input and output signals. Results are presented in the form of analysis of estimated parameter by comparing them with original parameter of the system.

- *The direct approach* in which a direct identification of the continuous-time parameters is made and in which some approximation of the differential operator is required. The estimation of the parameters by the direct approach may give rise to biased estimates, due to the approximation involved in the description of differential operator in discrete-time. An example of the description is presented in Section i.vi.

i.iii Approximation of derivative operator

In the mathematical description of dynamic systems, the derivative is used for the description of the response of a system to its inputs. In graphical representation, the derivative at a point for a real valued mathematical description is equal to the slope of tangent line. The process of derivation is described by derivative operator. Approximation of derivative operator in the description of continuous-time models has been an important milestone in the history of the parameters estimation in continuous-time. Many different algorithms have been proposed and in use for approximation of derivative operator. An overview of a few algorithms is described in this section.

The modulating function algorithm was first proposed by Shinbrot in [25,26]. The description of modulating function algorithm as in [26] is given next.

Consider a first order differential equation

$$a\frac{\mathrm{d}y(t)}{\mathrm{d}t} + y(t) = bu(t). \tag{1}$$

Assume that the input and the output signals are available for time interval $\{0, t_0\}$ and define a set of modulating functions

$$\varphi_n(t), \quad n = 1, 2, \ldots, t \in \{0, t_n\}, \tag{2}$$
$$\varphi_n(0) = \varphi_n(t_0) = 0. \tag{3}$$

Multiply the differential equation (1) with $\varphi_n(t)$ and integrate over $\{0, t_0\}$

$$a\int_0^{t_0} \varphi_n(t)\frac{\mathrm{d}y(t)}{\mathrm{d}t}\,\mathrm{d}t + \int_0^{t_0} \varphi_n(t)y(t)\,\mathrm{d}t = b\int_0^{t_0} \varphi_n(t)u(t)\,\mathrm{d}t. \tag{4}$$

Integrate first term by parts

$$\int_0^{t_0} \varphi_n(t)y(t)\,\mathrm{d}t - a\int_0^{t_0} \frac{d\varphi_n(t)}{\mathrm{d}t}y(t)\,\mathrm{d}t = b\int_0^{t_0} \varphi_n(t)u(t)\,\mathrm{d}t, \tag{5}$$

where the terminal conditions are used. Further that, the Fourier transform method or the Laplace transformation method can be applied at (5) to estimate the parameter by using the least squares solution. The algorithm is successfully implemented in many applications see for example [27–30]. In [27], the algorithm is applied to parameter estimation of a multivariable system. In [28], the algorithm is applied to recursive parameter estimation of continuous-time systems. In [29], time-varying system identification is made for the application prospective to a bio process that is fermentation process, and in [30], a parameter estimation for an aerodynamic system is made.

The Poisson moment function is another algorithm, which is widely used, for example in [31–33]. The description of the algorithm is given in [33], and repeated in Figure 2, where a chain filtration of the signals is made with a filtration process described by $1/s$. A linear continuous-time system described by the differential equation is considered as

$$\sum_{i=0}^{N} a_i p^i y(t) = \sum_{j=0}^{M} b_j p^j u(t), \tag{6}$$

where $y(t)$ is the output signal and $u(t)$ is the excitation signal with $p^i y(0)$ and $p^j u(0)$ being initial conditions and a_i and b_j being the system parameter. A Laplace transform of (6) is made as

$$\sum_{i=0}^{N} a_i s^i Y(s) = \sum_{j=0}^{M} b_j s^j U(s), \tag{7}$$

and the chain filtration process is implemented as described in Figure 2, where the

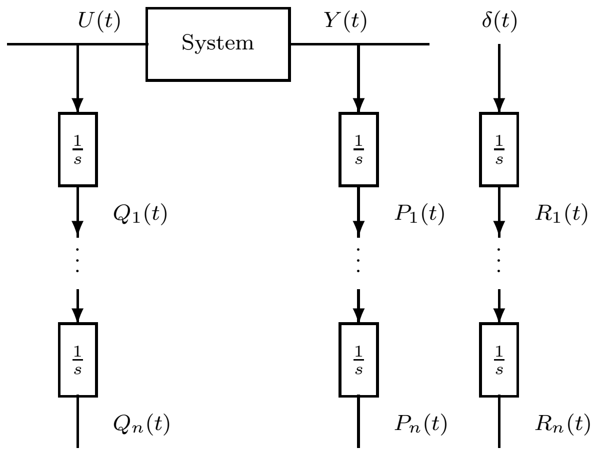

Figure 2: Description of the Poisson moment function for system identification as in [33].

maximum value of $N-1$ is used for the filtration chain. An inverse transform of the filtered signals is made and the model is re-arranged in terms of system parameter. The parameters are estimated by the least squares method. Similarly, in [31] the algorithm is used to identify a linear time-varying dynamic processes and in [32], the algorithm is used to identify a continuous-time systems.

The performance of repeated integration in the original differential equation is another algorithm, which removes all the derivatives. The algorithm has been applied successfully in parameter estimation algorithms, which was initially used in [34–36]. An illustration of the algorithm as in [34] is given as.

Consider the system

$$b_1 \frac{\mathrm{d}y(t)}{\mathrm{d}t} + y(t) = ku(t), \tag{8}$$

with transfer function

$$H(s) = \frac{R(s)}{F(s)} = \frac{K}{b_1 s + 1}. \tag{9}$$

The parameters to be estimated are K and b_1, where $u(t)$ is for the input signal and $y(t)$ is the output signal. The system described by (8) is integrated from 0 to t_1 and from 0 to t_2

$$b_1 \int_0^{t_1} y(t)\,\mathrm{d}t + \int_0^{t_1}\int_0^{t_1} y(t)\,\mathrm{d}t^2 = K \int_0^{t_1}\int_0^{t_1} u(t)\,\mathrm{d}t^2, \tag{10}$$

$$b_1 \int_0^{t_2} y(t)\,\mathrm{d}t + \int_0^{t_2}\int_0^{t_2} y(t)\,\mathrm{d}t^2 = K \int_0^{t_2}\int_0^{t_2} u(t)\,\mathrm{d}t^2. \tag{11}$$

A least squares estimator can be formed from (10) and (11) for the unknown parameters. Major developments were made towards sampled signals and digital filters by using this algorithm. Moreover the problems of bias compensation were studied as in [37–39].

Another important development is the orthogonal function algorithm used for repeated integrals, in which the process is represented by a series of orthogonal functions $\{\varrho_i(t), \quad i = 1, 2, \ldots, \infty\}$. The description of the algorithm as in [15] is given next.

Consider the orthogonal function expansion to the first two components of the output signal $y(t)$ and the input signal $u(t)$ involved in system description

$$y(t) \simeq y_1\varrho_1(t) + y_2\varrho_2(t), \tag{12}$$

$$u(t) \simeq u_1\varrho_1(t) + u_2\varrho_2(t), \tag{13}$$

and insert this in the description of the system

$$Y(s) = \frac{b}{(1+as)}U(s), \tag{14}$$

to get following results

$$ay(t) - ay(0)s(t) + \int_0^t y(\tau)d\tau = b\int_0^t u(\tau)d\tau, \qquad 0 \leqslant t \leqslant t_0, \tag{15}$$

where $s(t)$ is the description of unit step at $t = 0$, having spectral components of s_1 and s_2. Let

$$\int_0^t \varrho_1(\tau)d\tau \simeq e_{11}\varrho_1(t) + e_{12}\varrho_2(t), \tag{16}$$

$$\int_0^t \varrho_2(\tau)d\tau \simeq e_{21}\varrho_1(t) + e_{22}\varrho_2(t). \tag{17}$$

The integrals equation (16) and (17) are transformed to algebraic form to get the measurement matrix

$$\begin{bmatrix} y(0)s_1 - y_1 & u_1e_{11} + u_2e_{21} \\ y(0)s_2 - y_2 & u_1e_{12} + u_2e_{22} \end{bmatrix}, \tag{18}$$

and the output measurement vector is represented as

$$\begin{bmatrix} y_1e_{11} + y_2e_{21} \\ y_1e_{12} + y_2e_{22} \end{bmatrix}. \tag{19}$$

The major developments of the approach of orthogonal function are given in the survey [40] and the approach spurred a considerable interest [14,41].

The derivative approximation in the presence of noise has important applications in many field of engineering and applied mathematics. Many approaches have been proposed on the derivative approximation in the presence of noise [42–46]. Some other approaches for the derivative approximation and hence for the identification of continuous-time system also exist, for example the subspace method [12,13]. The approach based on replacing the differential operator p. In [47] , $p^l f(t_k)$ is approximated with a finite difference operator D_k^l. The approximation is described as

$$D_k^l f(t_k) = p^l f(t_k) + \mathcal{O}(h^s), \tag{20}$$

for a smooth function $f(t_k)$, where the weights $c_{l,k,u}$ must be chosen so that

$$D_k^l f(t_k) = \sum_{\mu=\mu_1}^{\mu_2} c_{l,k,u} f(t_{k+\mu}). \tag{21}$$

An example for (21) with $l = 2, \mu_1 = 0, \mu_3 = 3,$ and $s = 2$ is given as,

$$D_k^2 f(t_k) = c_{2,k,0} f(t_k) + c_{2,k,1} f(t_{k+1}) + c_{2,k,2} f(t_{k+2}) + c_{2,k,3} f(t_{k+3}), \tag{22}$$

where the weights $\{c_{2,k,\mu}\}_{\mu=0}^3$ for the sampling interval $\zeta_k(\mu) = t_{k+\mu} - t_k$ are chosen as the solution to

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ \zeta_k(0) & \zeta_k(1) & \zeta_k(2) & \zeta_k(3) \\ \zeta_k^2(0) & \zeta_k^2(1) & \zeta_k^2(2) & \zeta_k^2(3) \\ \zeta_k^3(0) & \zeta_k^3(1) & \zeta_k^3(2) & \zeta_k^3(3) \end{bmatrix} \begin{bmatrix} c_{2,k,0} \\ c_{2,k,1} \\ c_{2,k,2} \\ c_{2,k,3} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 2 \\ 0 \end{bmatrix}. \tag{23}$$

i.iv Models of continuous-time systems

Generally, the application of the specific identification method is associated with the specific structure of the continuous-time systems. An overview of the structures of the continuous-time systems investigated in later parts is presented here. The continuous-time systems can be categorized into two main branches; deterministic systems and stochastic systems [48].

A dynamic system in which the relationship between the states and the events can be precisely measured and where given input always produces the same output is defined as a deterministic system. The model

$$A(p)y(t) = B(p)u(t), \tag{24}$$

gives a general description of a continuous-time deterministic systems, where

$$A(p) = \sum_{i=0}^{n} a_i p^{n-i}, \quad B(p) = \sum_{i=1}^{m} b_i p^{m-i}, \tag{25}$$

and where p denotes the differentiation operator, $a_0 = 1$, and $m \leqslant n$, with n and m known. The parameter vector for the model (24) is

$$\boldsymbol{\theta}_0 = \begin{bmatrix} a_1 & \cdots & a_n & b_1 & \cdots & b_m \end{bmatrix}^T. \tag{26}$$

A continuous-time system can also be described by a state-space model. The state-space representation corresponding to the model (24) is

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}u(t), \tag{27}$$

$$y(t) = \mathbf{C}\mathbf{x}(t), \tag{28}$$

where $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ are the matrices of appropriate sizes. See, for example, [49] for further material on deterministic continuous-time systems.

A dynamic system having non-deterministic behavior in which the relationship between the states and the events can not be precisely determined, where the state is determined both by the predictable actions and by a random element is defined as a stochastic system. One general description of such a system is the continuous-time autoregressive-moving-average-exogenous (ARMAX) process

$$A(p)y(t) = B(p)u(t) + C(p)w(t), \tag{29}$$

where

$$A(p) = \sum_{i=0}^{n} a_i p^{n-i}, \quad B(p) = \sum_{i=1}^{m} b_i p^{m-i}, \quad C(p) = \sum_{i=1}^{r} c_i p^{r-i}, \tag{30}$$

with $a_0 = 1$, where p denotes the differentiation operator and $w(t)$ a continuous-time white noise source with incremental covariance Σdt. The state-space representation corresponding to the continuous-time ARMAX model (29) is the stochastic differential equation

$$\mathrm{d}\mathbf{x}(t) = \mathbf{A}\mathbf{x}(t)\,\mathrm{d}t + \mathbf{B}u(t) + \mathrm{d}\mathbf{w}(t), \tag{31}$$

$$y(t) = \mathbf{C}\mathbf{x}(t), \tag{32}$$

where $\mathbf{A}, \mathbf{B}$, and $\mathbf{C}$ are matrices of appropriate sizes.

Continuous-time stochastic systems are treated thoroughly in, for example, [50–52]. Note that the model (29) is described as a continuous-time ARMA model for $B(p) = 0$. The parameter vector for the model (29) is

$$\boldsymbol{\theta}_0 = \begin{bmatrix} a_1 & \cdots & a_n & b_1 & \cdots & b_m & c_1 & \cdots & c_r \end{bmatrix}^T. \tag{33}$$

In a general continuous-time model

$$\dot{\mathbf{x}}(t) = \frac{\mathrm{d}\mathbf{x}(t)}{\mathrm{d}t} = \boldsymbol{\alpha}\mathbf{x}(t) + \boldsymbol{\beta}e(t), \tag{34}$$

where $e(t)$ is a continuous-time white noise process with zero mean and constant spectrum. This white noise process has no physical existence due to infinite variance and mathematically relies on generalized functions. Therefore, the stochastic differential equation

$$\mathrm{d}\mathbf{x}(t) = \boldsymbol{\alpha}\mathbf{x}(t)\,\mathrm{d}t + \boldsymbol{\beta}\,\mathrm{d}W(t), \tag{35}$$

with $W(t)$ representing a Wiener process [53], is more formally used.

i.v Sampling of continuous-time model

The physical systems are observed in the discrete-time where these are obviously difficult to observe in the continuous-time. The process of describing the continuous-time models in terms of the discrete-time models is known as sampling, which gives the description of the observations at the discrete-time instances [10,51,52].

An example for the discrete-time description of the continuous-time ARMAX model (29) with the state space description in (31) and (32) is given as

$$\mathbf{x}(t_{k+1}) = \mathbf{F}\mathbf{x}(t_k) + \int_{t_k}^{t_{k+1}} \mathrm{e}^{\mathbf{A}(t_{k+1}-s)}\mathbf{B}u(s)\,\mathrm{d}s + v(t_k), \tag{36}$$

by assuming the input $u(t)$ and the output $y(t)$ from the continuous-time system observed at time instance $t_1, t_2, \cdots, t_N$, where

$$\mathbf{F} = \mathrm{e}^{\mathbf{A}h_k}, \tag{37}$$

with $h_k = t_{k+1} - t_k$, and where $v(t_k)$ is representing discrete-time white noise with zero mean and covariance matrix

$$\mathbf{R}(h_k) = \int_0^{h_k} \mathrm{e}^{\mathbf{A}s}\Sigma\mathrm{e}^{\mathbf{A}^T s}\,\mathrm{d}s. \tag{38}$$

i.vi A direct approach for parameter estimation

A description of a direct approach is given for the parameter estimation, in which a linear regression in formed and the parameters are estimated by using the least squares method. Consider, the model (24) which can be described in the linear regression form

$$y(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta}, \tag{39}$$

where the parameter vector $\boldsymbol{\theta}$ is defined in (26) and the regression vector $\boldsymbol{\varphi}(t)$ is described as

$$\boldsymbol{\varphi}^T(t) = \begin{bmatrix} -p^{n-1}y(t) \\ -p^{n-2}y(t) \\ \vdots \\ -y(t) \\ p^m u(t) \\ p^{m-1}u(t) \\ \vdots \\ u(t) \end{bmatrix}. \tag{40}$$

Here, an approximation of the differential operator p is required for the discrete-time sampled data. One possible approximation is given by the difference operator D_k^l in (21). The parameter vector $\boldsymbol{\theta}$ can be estimated by the least squares method described in Section i.vii. Note that, this approach can be implemented on-line [24,54,55] as

$$\hat{\boldsymbol{\theta}}(t_k) = \hat{\boldsymbol{\theta}}(t_{k-1}) + \boldsymbol{K}(t_k)\left(y(t_k) - \boldsymbol{\varphi}^T(t_k)\hat{\boldsymbol{\theta}}(t_{k-1})\right), \tag{41}$$

where $\hat{\boldsymbol{\theta}}(t_k)$ is the estimate of $\boldsymbol{\theta}$ at time t_k,

$$\boldsymbol{K}(t_k) = \boldsymbol{P}(t_{k-1})\boldsymbol{\varphi}(t_k)\left(\lambda + \boldsymbol{\varphi}^T(t_k)\boldsymbol{P}(t_{k-1})\boldsymbol{\varphi}(t_k)\right), \tag{42}$$

and

$$\boldsymbol{P}(t_k) = \frac{\boldsymbol{P}(t_{k-1}) - \boldsymbol{P}(t_{k-1})\boldsymbol{\varphi}(t_k)\boldsymbol{\varphi}^T(t_k)\boldsymbol{P}(t_{k-1})\left(\lambda + \boldsymbol{\varphi}(t_k)^T\boldsymbol{P}(t_{k-1})\boldsymbol{\varphi}(t_k)\right)^{-1}}{\lambda}, \tag{43}$$

where λ is a forgetting factor.

i.vii Minimization by the least squares method

The least squares method also known as the curve fitting method. In least squares method the estimate of the parameter vector $\boldsymbol{\theta}$ is determined by minimizing the sum of the squares for the prediction error $e(t_k, \boldsymbol{\theta})$ [56–58]. The prediction error is described as

$$\mathrm{e}(t_k, \boldsymbol{\theta}) = \hat{y}(t_k) - y(t_k), \tag{44}$$

for the prediction

$$\hat{y}(t_k) = \varphi^T(t_k)\boldsymbol{\theta}, \tag{45}$$

which depends upon the unknown parameter $\boldsymbol{\theta}$ for the past data $\mathbf{Z}^k$, where

$$\mathbf{Z}^N = \{u(1), y(1), \cdots, u(N), y(N)\}. \tag{46}$$

The minimization of the sum of the norms is made as

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} V(\boldsymbol{\theta}, \mathbf{Z}^N), \tag{47}$$

where

$$V(\boldsymbol{\theta}_0, \mathbf{Z}^N) = \frac{1}{N}\sum_{t=1}^{N} \mathrm{e}^2(t_k, \boldsymbol{\theta}), \tag{48}$$

and where $\hat{y}(t_k)$, is linear in $\boldsymbol{\theta}$ and the $V(\boldsymbol{\theta}, \mathbf{Z}^N)$ is quadratic. The minimization problem (47) can be minimized analytically to get the least squares estimate

$$\hat{\boldsymbol{\theta}}_{LS} = \left[\sum_{k=1}^{N} \boldsymbol{\varphi}(t_k)\boldsymbol{\varphi}^T(t_k)\right]^{-1} \sum_{k=1}^{N} \boldsymbol{\varphi}(t_k)y(t_k). \tag{49}$$

provided the inverse exist.

ii Networked control systems

Revolutionary achievements have been made in the fields of wireless communication, the internet, and the microelectronics over the past decades. Many devices have been developed that can communicate with each other, can sense, compute and control many features internally and externally within integrated systems, see literature [59–63]. For example, wireless sensors and actuator networks (WSANs) refer to a group of sensors and actuators linked by a wireless medium. Networked control systems are flourishing recently [64] and are used in many applications. In military applications, the wireless networks are integral part of military command, control, communication, computing, intelligence, surveillance, reconnaissance and targeting (C4ISRT) systems. In environmental protection networked control systems are used for forest fire detection [65], bio-complexity mapping [66] and flood detection [67]. In healthcare, networked control systems are used for telemonitoring of human physiological data [68] and drug administration in hospitals [69]. In home applications networked control systems are used for home automation to interact between home appliances such as vacuum cleaner, VCR, refrigerator and other appliances [70]. Networked control systems are used for smart environment in which the server, sensors and nodes can be integrated with room appliances to become self organized, self regulated and adaptive based on the control system [71]. Numerous examples of applications of networked control systems are found in the literature, see for example [62,72] and the references therein. Major challenges in this field are communication constraints, packets losses and random time-delays in the wireless communication [72]. Stability of networked control systems is another challenge, which has been thoroughly studied, see for example [73,74]. An important advantage of using networked control systems in different applications is reduction in cost of designing, implementation and modification [60].

In networked control systems the sensors and the actuators communicate with remotely placed controller over the network, and improved techniques are needed for the state estimation to get the closed-loop stability. Some early results were given by Shannon on the maximum bit rate that a channel can carry with reliability [75, 76]. A significant research has been made to the problem of determining the minimum bit rate to get a stabilized networked control system, for example, [77–79] are on stability of linear systems and [80, 81] are on stability of non linear systems through feedback over a network.

The parameter estimation problem in different networked configurations has not been studied extensively in the literature but [82–86] are examples of papers partly or completely devoted to identification. System identification for networked control is considered and different estimation concepts are applied to networked control systems.

ii.i An overview

The functionality of a networked control systems is based on the following four basis elements.

- *Sensor.* A sensor act as a converter which measures a physical quantity for any dynamic process and converts it to a signal readable by an electronic instrument.
- *Controller.* A controller is used to provide decisions and commands. In networked control systems, a controller is used for monitoring a dynamic system and for changing the operating conditions of the dynamic system.
- *Actuator.* An actuator is used to perform the control and decision commands received from the controller at the dynamic system.
- *Communication channel*. The communication channel is used for exchange of information from the sensor to the controller and from controller to the actuator.

A typical single-loop configuration of a networked control system in which the structure is composed of a controller, a remote plant containing a dynamic system, a sensor and an actuator, is schematically shown in Figure 3. The controller and the plant are considered physically located at different locations and linked by a communication channel for a remote closed-loop control. The control signal is considered encapsulated in a packet or a frame which is sent to the plant by using the communication network.

The actuator in a typical single loop networked control system as depicted in Figure 3, can be described by a decoder block and a hold block where the decoder is also known as de-quantizer. Similarly, the sensor can also be described by an encoder or by a quantizer. A continuous-time system in a networked environment can be

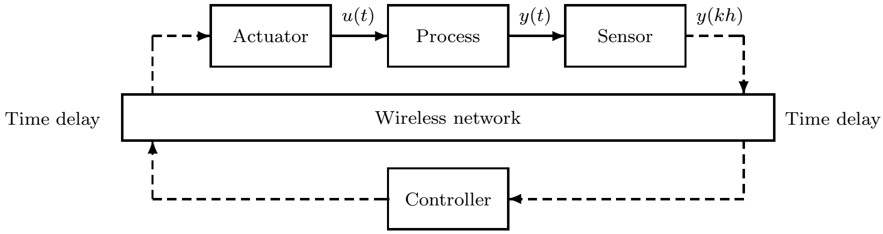

Figure 3: A networked control system.

described by (27) and (28). The discretization of a continuous-time system in a networked environment can be made with unform sampling h and with zero-order hold. The discrete-time equivalent of the system in the networked environment is given as

$$\mathbf{x}(kh + h) = \mathrm{e}^{\mathbf{A}h}\mathbf{x}(kh) + \int_0^h \mathrm{e}^{\mathbf{A}\sigma}\,\mathrm{d}\sigma\mathbf{B}u_k, \tag{50}$$

$$\mathbf{y}(kh) = \mathbf{C}\mathbf{x}(kh), \tag{51}$$

where quantization effects are neglected.

ii.ii Major issues

In recent years many technological advantages of networked controlled systems that result in decreased cost and size, have promoted the use of cost effective interconnected systems with increasing computational, sensing, monitoring and adaptive capabilities [60]. However, the communication over a network environment also has its problems of affecting the stability of the control system or affecting the performance of a networked control system [72]. Some major issues affecting the performance of a networked control system are given next [87,88]:

- *Time-delays*. The communication network generally causes random time-delays for the transmission of data. These delays are composed of transmission delays, queuing delays, propagation delays and computational delays [88].
- *Fading*. Fading is a common problem in wireless communication. In [89] fading is modeled by multiplicative uncertainty and addressed by robust control technique.
- *Packet drops*. The problem with packet drops in which data packets are lost in the communication network is of main concern. The main reasons for the packet drops are congestion due to high bit rate in the networked environment, detection error or delayed arrival at the receiver, and unavailability of the network for a long time for the data transition.

- *Limited bit rate*. The capacity of a networked control system is consumed by different agents connected to networks, thus impose restriction of low bit allocation to the system.

The most significant problems for the parameter estimation are the time-varying delays and the packets losses in the networked control system.

iii Errors-in-variables systems

In statistics, regression analysis is a technique used for the physical systems to estimate the relationship between different variables. The standard forms of the regression analysis either are all those models having exact measured signals or are all those models having measurement errors. The case of the regressor analysis having measurement errors are described by errors-in-variables systems. In errors-in-variables systems the parameter estimation made under standard form without considering the measurement noises can lead to inconsistent results. The description of theory, applications, the latest research and advances in the field is given in the book [90]. The background motivation and examples in system identification with detailed overview of errors-in-variables problem in which the input signal samples and the output signal samples are corrupted by noise is given in [91]. Some analysis, algorithms and applications in engineering for errors-in-variables systems are found in [92].

Many algorithms for estimation of parameter have been proposed for this problem. The estimation of a causal linear dynamic system is made in [93] where the system is excited by noise of unknown spectrum. The set membership errors-in-variables identification problem is considered in [94], where the input and the output are corrupted by bounded noise. A subspace identification algorithm is given in [95] for errors-in-variables problem and recursive algorithms are considered towards errors-in-variables problem in [96]. Moreover, the extension of the Frisch scheme is made towards errors-in-variables problem in [97]. The eigenvector analysis of joint covariance matrix of the observations is used in [98] to estimate the parameters of multiple input multiple output systems and the parameters of linear multiple input the multiple output errors-in-variables problems are estimated in [99] by change point in the data. Errors-in-variables system identification has an important application in aircraft flutter parameter identification, where improved accuracy of model parameter estimation is required while dealing with noisy data. Many different methods are proposed for analysis of aircraft flutter, for example the numerically robust frequency domain estimator in [100] and least squares estimator with vector orthogonal polynomials in [101]. Errors-in-variables problems has its applications in many other fields, for example, biomedicine, finance, chemical engineering, image systems, econometrics, mechanical and electrical engineering, geoscience, and time series analysis. The covariance matching method in which parameters are estimated by means of second order properties by matching covariance and cross-covariance functions and in which an expression is derived for the asymptotic covariance matrix is proposed in [102,103] and [104].

Errors-in-variables system identification has been widely discussed in the past and also considered in recent proceedings [105–107]. In [105], the model order of errors-in-variables estimation problem is determined by using four different approaches along with a discussion for the comparison of these approaches. In [106], errors-in-variables problem with mutually correlated input and output noises is considered, where the criterion relies on a high order Yule-Walker equation. In [107], an estimation algorithm is proposed using incomplete data for errors-in-variables systems represented by a transfer function. A comparison of the proposed technique with frequency domain system identification techniques applied to errors-in-variables systems is made.

The continuous-time errors-in-variables system identification problem is less studied in the literature, but [102, 104, 108–113] are examples of papers dealing with this problem. In [108], four different methods are considered; a method of parallel input-output modeling, a Shinbrot moment functionals method, a covariance matching method, and a prediction error method. An analysis of a covariance matching approach is made in [102], assuming the noise-free input signal as a continuous-time ARMA process, whose parameter is estimated together with the system parameter. A more general expression is proposed for covariance matching for estimation of errors-in-variables system parameters in [104], in which the continuous-time parameters of the single input single output errors-in-variables system are estimated in [104]. A direct approach is taken in [109] and noise effects on the state-variable filter outputs are analyzed, resulting in a suggestion of consistent parameter estimators. Maximum likelihood estimation in the frequency domain is considered in [110]. Third-order cumulants based methods are presented in [111], and a covariance matching method in which the input signal is not explicitly modelled is suggested in [112] and analyzed in [113].

iii.i An overview

A description of the errors-in-variables problem is depicted in Figure 4, in which available input and output signals corrupted by additive noises. Evaluation of errors-in-variables problem is based on noise corrupted available signals. The system of errors-in-variables problem can be described as

$$A(p)y_0(t) = B(p)u_0(t), \tag{52}$$

where $y_0(t)$ is the noise free output and $u_0(t)$ is the noise free input and where $A(p)$ and $B(p)$ are described in (25). The observations from the system are corrupted by additive noises $\tilde{y}(t)$ and $\tilde{u}(t)$, and measured as

$$y(t) = y_0(t) + \tilde{y}(t), \tag{53}$$

$$u(t) = u_0(t) + \tilde{u}(t). \tag{54}$$

In errors-in-variables system identification, the assumptions on the system, the measured input, the measured output and the noise properties are important. Assumptions in errors-in-variables system identification are made to get the consistency of the estimates from different realizations. In classical deterministic problems where the inputs and the outputs are measured without error. The assumptions on the noise generally have negligible effect on the consistency of the estimates, but can affect the accuracy of the results. On the other hand the assumption on noise in the errors-in-variables problem can have significant consequences on the estimated parameters. A general set of assumptions for errors-in-variables problem are described as:

- The dynamic system is assumed asymptotically stable.
- The noise process $\tilde{y}(t)$ and $\tilde{u}(t)$ are mutually uncorrelated and these are uncorrelated with the noise free output $y_0(t)$ and the input $u_0(t)$ signals.
- Assumptions on the first and the second order statistical properties of the noise process $\tilde{y}(t)$ and $\tilde{u}(t)$ are made in terms of the mean and the variance of noise processes.

In general, some difficulties arises in errors-in-variables system identification due to noise processes $\tilde{y}(t)$ and $\tilde{u}(t)$. The traditional methods used for identification of errors-in-variables problem may completely fail or give non-consistent and biased results, since they consider only the output noise. Errors-in-variables system identification can be made by introducing extra assumptions on the output $y_0(t)$, the input $u_0(t)$, the process $\tilde{y}(t)$, $\tilde{u}(t)$ and the system. For example, known mean and variance of the noise, and known order of the system model. Generally, some assumption of the poles and zeros are also introduced that is, they are not shared by different transfer function [114].

The statistical efficiency of a parameters estimator in errors-in-variables problem can be accessed by the Cramér-Rao lower bound (CRB), which is the lower bound for the covariance matrix of the estimates of the parameters [115, 116]. The description of CRB is given as

$$\text{cov}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) \geqslant \text{CRB} = J^{-1}, \tag{55}$$

where

$$J = \text{E}\left(\frac{\partial \text{Log} L(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right)^T \left(\frac{\partial \text{Log} L(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right), \tag{56}$$

where matrix J is described as the Fisher information matrix and $L(\boldsymbol{\theta})$ is the likelihood function. The result is applicable to any unbiased parameters estimator in system identification.

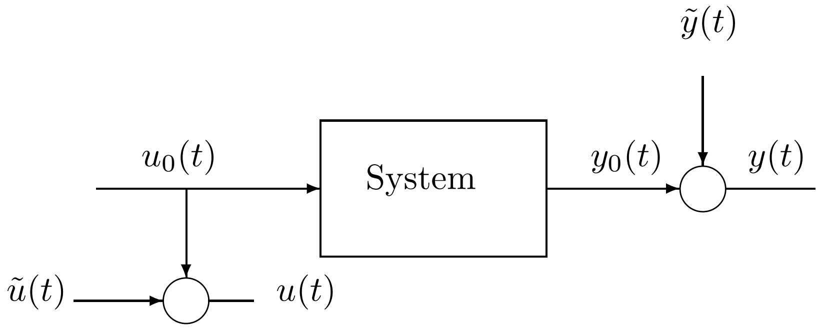

Figure 4: A description of an errors-in-variables system as in [91]. The noise free input to the system is $u_0(t)$ and the noise free output from the system is $y_0(t)$. The available signals are the input $u(t)$ and the output $y(t)$ and these signals are corrupted by unknown additive noises, respectively given as $\tilde{u}(t)$ and $\tilde{y}(t)$.

In [116], three main classification of parameters estimation techniques are described for errors-in-variables problems. First classification is based on using covariance matrix in which instrument variables, bias-eliminating least squares, the Frisch scheme, and total least squares are included. In this classification all approaches are based on the covariance elements $\hat{r}_u(\tau)$, $\hat{r}_y(\tau)$, and $\hat{r}_{yu}(\tau)$. Second classification, is based on the spectrum of the input and the output signals and frequency domain data. See [117] for a general description of frequency domain estimators for errors-in-variables problems. Third classification, is based on time-series data, in which prediction error and maximum likelihood techniques are included.

iv Wireless channel modeling

The description of the dynamics of a scattered electric field is historically given by a well-known Clarke's model [118], in which the phases are assumed to be constant throughout the multi-path received component of the wireless channel. The modeling, estimation and identification of mobile-to-mobile communication channels by stochastic differential equations is an important research field in current decade [119, 120]. A description of a wireless channel is depicted in Figure 5, where an electromagnetic signal is injected to the environment by a transmitter and is remotely received at the receiver. The multiple nonstationary objects in the environment around the transmitter and the receiver create multi-paths effect in the wireless channel. A change in carrier frequency of the electromagnetic signal is observed in the form of a Doppler frequency by the observer that is, when the receiver is moving relative to the transmitter.

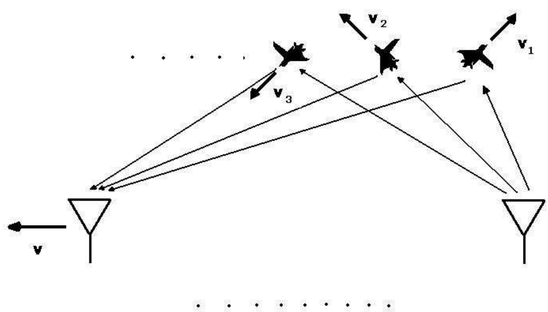

Figure 5: A description of a wireless channel in which an electromagnetic signal is injected to the environment by a transmitter and remotely received at the receiver. The presence of multiple stationary or nonstationary objects in the environment around the transmitter and the receiver create multi-paths.

The received signal $r(t)$ at a moving receiver is described as [121]

$$r(t) = \text{Re}\left\{\sum_{k=1}^{P} A_k e^{i(2\pi f_k t + 2\pi f_c (t-\tau_k))}\right\}, \tag{57}$$

where P is the number of signal paths, f_c is the carrier frequency of the baseband signal, and τ_k, f_k and A_k are the corresponding time-delay, the Doppler frequency and the strength, respectively, for path k. The received signal becomes

$$r(t) = \text{Re}\left\{\mathsf{E}(t) e^{i2\pi f_c t}\right\} = \mathsf{E}_I(t)\cos(2\pi f_c t) - \mathsf{E}_Q(t)\sin(2\pi f_c t), \tag{58}$$

where $\mathsf{E}_I(t)$ and $\mathsf{E}_Q(t)$ are the in-phase and quadrature components given by

$$\mathsf{E}_I(t) = \sum_{k=1}^{P} A_k \cos(2\pi f_k t - 2\pi f_c \tau_k), \tag{59}$$

$$\mathsf{E}_Q(t) = \sum_{k=1}^{P} A_k \sin(2\pi f_k t - 2\pi f_c \tau_k). \tag{60}$$

The covariance function of $\mathsf{E}_I(t)$ and $\mathsf{E}_Q(t)$ gives a description of a zeroth order Bessel function [122], which is described as

$$J_0(x) = \frac{1}{\pi}\int_0^{\pi} \cos(x\sin(\tau))\,\mathrm{d}\tau. \tag{61}$$

In [123], Clarke's model is extended for the time-varying nature of the wireless chan-

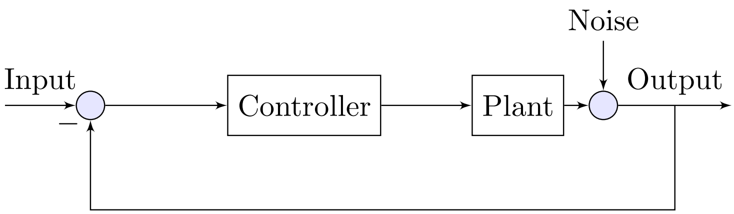

Figure 6: A basic description of a plant in a closed-loop.

nel by introducing Wiener processes to represent the time-varying phases. In [124], a wireless channel is modeled based on a stochastic differential equation for the case of a fixed Doppler shift. Moreover, in [125], the time-varying nature of the wireless channel is described by Wiener processes for a statistical analysis of an extended Clarke's model.

v Closed-loop identification

Historically, the problem of identification of a plant in a closed-loop is of considerable interest. One of the earliest contributions in this field is by Akaike [126], in which varies aspects of this problem has been studied. Subject of closed-loop system identification has been actively pursued in the seventies, and is summarized in the survey paper [127]. The problem has been discussed in [127–129], where different approaches have been used for the identification of a plant in a closed-loop. In the survey paper [130], many results are given. The subject of identification of the plant in a closed-loop is partially or completely discussed in the recent proceedings [21, 22, 131, 132]. In [131], the problem of closed-loop system identification is considered in the presence of bounded noise. In [132], the input to the closed-loop is designed while considering the cost minimization for identification while meeting the desired specifications on the quality of the identified model. In [22], off-line output error identification algorithms are presented for linear continuous-time systems with unknown time-delay from sampled data operating in open-loop and in closed-loop. In [21], a continuous-time model identification of closed-loop Hammerstein-Wiener system with unknown controller is made, different noise situations are studied and an identification algorithm is proposed which is based on the instrumental variable method.

The structure of a closed-loop system is described by a controller, a plant, a feedback loop, the input signal and the output signal. History of control theory has important implication on the history of closed-loop system and many concepts related to control theory are found in [49]. The era between 1930's to 1960's is known as classical control period. Theories by Nyqvist and Bode played important role for the design and the control of systems in terms of stability and robustness of systems with the single input and the single output. The control theory was based on the frequency domain interpretation and many methods were graphical for the description of control systems, for example, Bode Plots, Nyqvist plots, Nichols charts and root locus plots. The Gain margins and the phase margins were used to analyze the robustness of the control system design. The controllers were of PI and PID type. A description of a PID controller is given next

$$u(t) = K_p e(t) + K_i \int_0^t \mathrm{e}(\tau)\,\mathrm{d}\tau + K_d \frac{\mathrm{de}(t)}{\mathrm{d}t} \tag{62}$$

where K_p is the proportional gain, K_i is the integral gain, K_d is the derivative gain and $e(t)$ is the instantaneous error.

Kalman's contribution on state-space models during late 1950's to early 1960's gave birth to a new era in control theory referred to as optimal control period. New concepts, for example, optimal state feedback, optimal state estimation, controllability and observability were introduced. Moreover, the concepts of linear quadratic control and certainty equivalence control were introduced. In the beginning of the 1980's H_∞ method was introduced to model the uncertainties in the controller design, which gave rise to modern control or the robust control era. The concepts of robust stability and the robust performance were introduced in the modern robust control methods. Moreover, in parallel to these methods the adaptive control methods were also introduced in the field of control theory.

In closed-loop system identification, the parameters of the plant are estimated, where the plant is controlled in a closed-loop. A simple configuration of a closed-loop system is depicted in Figure 6. The plant in the closed-loop is controlled by the controller, where the controller is in the feed-forward loop. The output signal and the feedback signal is also corrupted by the noise signal. Many different configurations of closed-loop systems exist, depending upon the location of the plant, the controller and the noise signal within the closed-loop system.

vi Outline of different parts

vi.i Outline of Part II

A study on following topics is presented in this part:

A. Covariance function based approach.

B. Study of some estimation approaches.

A - Covariance function based approach

A covariance function based approach to the networked control system parameter estimation problem is presented in this contribution.

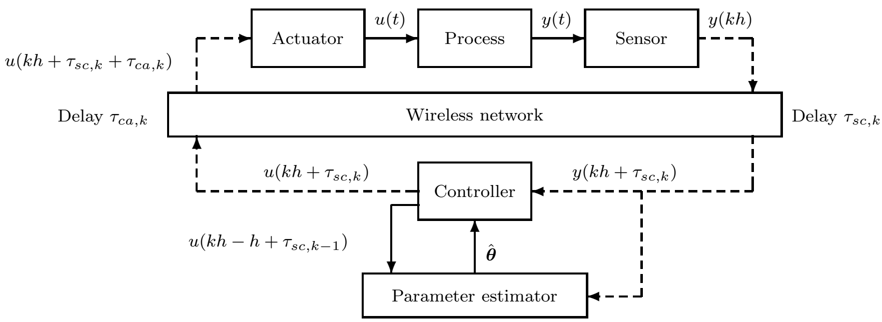

Figure 7: A networked control system with clock sampling.

A complete description of a networked control system is given in Figure 7. The networked control system is assumed having randomly distributed time-delays in the wireless links [60–63]. The time-delay from the sensor to the controller is described by $\tau_{sc,k}$ and the time-delay from the controller to the actuator is described by $\tau_{ca,k}$. The total time-delay from the sensor to the controller and then to the actuator is $\tau_k = \tau_{sc,k} + \tau_{ca,k}$.

A continuous-time description for the process of the networked control system is chosen since the random time-delays make it difficult to work with a discrete-time model; a time-varying model would be required to describe the discrete-time system. The process is described in transfer function form in continuous-time as

$$y(t) = \frac{B(p)}{A(p)}u(t), \tag{63}$$

where

$$A(p) = \sum_{i=0}^{n} a_i p^{n-i} = \prod_{i=1}^{n}(p-\alpha_i), \tag{64}$$

$$B(p) = \sum_{i=1}^{m} b_i p^{m-i}, \tag{65}$$

where p denotes the differentiation operator, $a_0 = 1$, and $m \leqslant n$, with n and m known. The process can also be described in state-space form (27)–(28).

The continuous-time model (63) for the process of the networked control system is discretized at the sensor by the sampling interval h, as illustrated in Figure 7. In [86] and [133] complete details on the discretization of a system in a networked environment with the clock sampling interval are given, where the discretization for small time-delays $\tau_k \leqslant h$ is described by

$$\mathbf{x}(kh+h) = e^{\mathbf{A}h}\mathbf{x}(kh) + \int_0^{h-\tau_k} e^{\mathbf{A}\sigma} d\sigma \mathbf{B} u_k + \int_{h-\tau_k}^{h} e^{\mathbf{A}\sigma} d\sigma \mathbf{B} u_{k-1}. \tag{66}$$

The number of equations for the description of the discrete-time model is increased to five for $0 \leqslant \tau_k \leqslant 2h$. An expression of the discrete-time model for a networked control system for $0 \leqslant \tau_k \leqslant 3h$ based on generalized expression [86, 133, 134] is given as

$$\mathbf{x}(kh+h) = \mathbf{F}\mathbf{x}(kh) + \left(\int_0^{h-t_{k,1}} \mathrm{e}^{\mathbf{A}\sigma}\mathbf{B}\,\mathrm{d}\sigma\right) u_k + \left(\int_{h-t_{k,1}}^{2h-t_{k,2}} \mathrm{e}^{\mathbf{A}\sigma}\mathbf{B}\,\mathrm{d}\sigma\right) u_{k-1}$$
$$+ \left(\int_{2h-t_{k,2}}^{3h-t_{k,3}} \mathrm{e}^{\mathbf{A}\sigma}\mathbf{B}\,\mathrm{d}\sigma\right) u_{k-2} + \left(\int_{3h-t_{k,3}}^{h} \mathrm{e}^{\mathbf{A}\sigma}\mathbf{B}\,\mathrm{d}\sigma\right) u_{k-3}, \tag{67}$$

where

$$t_{k,j} = \min \left\{ \begin{array}{c} \max\{0, \tau_{k+j-\bar{l}} + (j-\bar{l})h\}, \\ \max\{0, \tau_{k+j-\bar{l}+1} + (j-\bar{l}+1)h\}, \ldots, \\ \max\{0, \tau_{k-\underline{l}} - \underline{l}h\}, h \end{array} \right\}$$

for $j \in \{1, 2, 3\}$, where $\underline{l} = \tau_{\text{min}}/h$ and $\bar{l} = \tau_{\text{max}}/h$ are positive integers.

Depending upon the different sizes of the time-delays, i.e., the sizes of τ_k, τ_{k-1}, and τ_{k-2}, the integrals in (67) change their structure, where each specific set of time-delays of specific sizes form an equation for the discretized model. These specific sets of time-delays of specific sizes are segregated into different regions to formulate the total number of equations for the time-delays $0 \leqslant \tau_k \leqslant 3h$. The equations are dependent upon the values of τ_{max} and τ_{min} for different segregated regions of specific time-delays of specific sizes, where τ_{max} is the maximum time-delay and τ_{min} is the minimum time-delay in any region. A criterion to find these segregated regions of specific time-delays of specific sizes is described for a general case, followed by an illustration.

The choice of fictitious white noise samples as an input signal is made. An analysis of the noise samples sent from the controller and the noise samples received at the actuator is made. The degree of whiteness of the fictitious white noise samples sent from the controller is affected by the random time-delays. A statistical analysis of the fictitious input signal samples corresponding to the clock sampling instants is made. It turns out that this non-whiteness is related to the time-delays which can be described as a second-order moving-average MA(2) process for $\tau_k \leqslant 3h$. The sampled output signal is characterized by a standard ARMA$(n, n+l-1)$ model, where l is related to the size of the time-delays. The MA part of the sampled output signal depends in a complicated way on the system parameter and the statistical properties of the time-delays.

The proposed algorithm for estimation of parameters consists of two parts. In the first part, a discrete-time Yule-Walker equation is used to estimate the denominator polynomial parameter of the transfer function of the networked controlled system. In the second part, an equation relating the covariance function of the output signal and derivatives of the covariance function of the filtered input signal are used to estimate the numerator polynomial parameters of the system is the networked environment. The covariance function based approach is an appropriate choice for the estimation of parameters due to irregularities in the networked environment in the form for time-delays, as it relies on second order statistical properties, where the input signal samples are from a discrete-time white noise sequence. In particular, the method does not need to know the actual irregular time instants when new input signal levels are applied at the actuator.

B - Study of some estimation approaches

The contribution is on some estimation approaches for the system in the networked environment. The configuration of networked control system is given in Figure 7 for clock-sampling case. A continuous-time description for the system of networked control system is considered as in (63), since the discrete-time description is time-varying due to random time-delays. The discretization of the networked control system is proposed by two criteria described as:

- A commonly used clock sampling criteria, as described in (66) for small time-delays $\tau_k \leqslant h$.
- An irregular sampling criterion, which is described as follows

$$\mathbf{x}(\Lambda_{k+1}) = e^{\mathbf{A}\tau_k}\mathbf{x}(\Lambda_k) + \int_0^{\tau_k} e^{\mathbf{A}\sigma} d\sigma \mathbf{B} u(\Lambda_{k-1}), \tag{68}$$

  where

$$\Lambda_k = \Sigma_{i=1}^{k-1}\tau_i, \tag{69}$$

  and

$$\tau_{sc,k} = \underline{h} + \overline{\tau}_{sc}, \tag{70}$$

$$\tau_{ca,k} = \underline{h} + \overline{\tau}_{ca}, \tag{71}$$

  where $\tau_{sc,k} = \underline{h} + \overline{\tau}_{sc}$ and $\tau_{ca,k} = \underline{h} + \overline{\tau}_{ca}$ give τ_k. Furthermore, the stochastic variables $\overline{\tau}_{sc}$ and $\overline{\tau}_{ca}$ are in the respective intervals $\overline{\tau}_{sc} \in [0, \underline{h}\overline{h}]$ and $\overline{\tau}_{ca} \in [0, \underline{h}\overline{h}]$, defined by $\underline{h}$ and $\overline{h}$.

A comparison study of three estimation approaches is presented and an overview of these estimation concepts is depicted in Figure 8. Two strategies, clock sampling

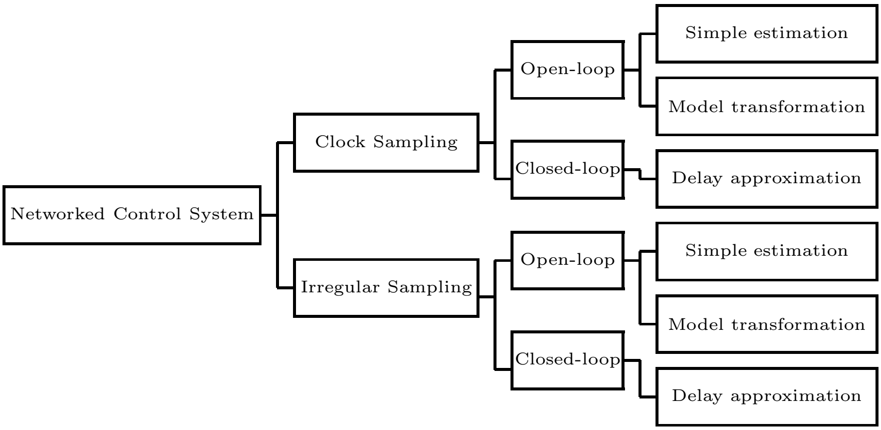

Figure 8: An overview of the estimation concepts and in which situations they are considered. All estimation concepts are considered for off-line and on-line situations.

and irregular sampling are considered for the discretization and two scenarios, open-loop and closed-loop are considered for how the system is studied. For the open-loop scenario, two parameter estimation concepts are applied whereas a third parameter estimation concept is applied for the closed-loop scenario. In the first estimation concept, the open-loop description of the networked control system is considered. The situation of the input acting at the actuator and the output received at the sensor is described as the open-loop description. The algorithm for the first estimation concept is exactly same as the algorithm described in the Section i.vi. In the estimation second concept, which is based on the model transformation where a reformulation of the transfer function by considering a casual and stable linear operator as in [135] is made to estimated the parameters. In the third concept, a closed-loop description of the networked control system is considered. The situation of the networked control system from the sensor to the controller and then to the actuator by including the time-delay is described by the closed-loop description. The time-delay in the closed-loop is approximated by a Padé approximation, a linear regression is formed and the parameters are estimated by least squares. Off-line as well as on-line implementations of all the parameter estimation concepts are considered. On-line implementation for the estimation of parameters is given in (42), which is respectively modified for the other approaches. The discretization strategies, observation scenarios and the parameter estimation concepts are relevant in different industrial applications involving networked control systems. Comprehensive simulation studies are presented.

vi.ii Outline of Part III

A study on following topics is presented in this part:

A. Estimation of errors-in-variables problem.

B. Accuracy of errors-in-variables estimation problem.

A - Estimation of errors-in-variables problem

In this contribution the continuous-time multiple input multiple output errors-in-variables systems identification problem is solved by means of covariance matching. A right matrix fraction description is considered for the transfer function, which is given as

$$\mathbf{y}_0(t) = \mathbf{B}(p)\mathbf{A}^{-1}(p)\mathbf{u}_0(t), \tag{72}$$

where $\mathbf{y}_0(t) \in \mathbb{R}^{n_y \times 1}$, $\mathbf{u}_0(t) \in \mathbb{R}^{n_u \times 1}$, and where $\mathbf{A}(p) \in \mathbb{R}^{n_u \times n_u}$ and $\mathbf{B}(p) \in \mathbb{R}^{n_y \times n_u}$ for $m \leqslant n$ are given as

$$\mathbf{A}(p) = \mathbf{I}_{n_u} p^n + \mathbf{A}_1 p^{n-1} + \cdots + \mathbf{A}_n, \tag{73}$$

$$\mathbf{B}(p) = \mathbf{B}_1 p^{m-1} + \cdots + \mathbf{B}_m, \tag{74}$$

where $\mathbf{I}_{n_u}$ is the identity matrix of size n_u.

Introduce

$$\mathbf{z}_0(t) = \mathbf{A}^{-1}(p)\mathbf{u}_0(t). \tag{75}$$

to form some covariance expression in terms of the unknown parameters. A derivation of generalized description is made for some covariance expression, which is expressed as

$$\mathbf{v}_{\mathbf{R}}(\tau) = \mathbf{G}(\boldsymbol{\theta})\mathbf{v}_{\mathbf{R}_{z0}}(\tau), \tag{76}$$

where

$$\mathbf{v}_{\mathbf{R}}(\tau) = \begin{bmatrix} \text{vec}(\mathbf{R}_{y_0}(\tau)) \\ \text{vec}(\mathbf{R}_{u_0}(\tau)) \\ \text{vec}(\mathbf{R}_{y_0 u_0}(\tau)) \\ \text{vec}(\mathbf{R}_{u_0 y_0}(\tau)) \end{bmatrix}, \tag{77}$$

$$\mathbf{v}_{\mathbf{R_{z0}}}(\tau) = \begin{bmatrix} \text{vec}(\mathbf{R}_{z_0}(\tau)) \\ \text{vec}(p\mathbf{R}_{z_0}(\tau)) \\ \vdots \\ \text{vec}(p^{2n}\mathbf{R}_{z_0}(\tau)) \end{bmatrix}, \tag{78}$$

$$\mathbf{G}(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{G}_{1,1} & \cdots & \mathbf{G}_{1,2m-1} & 0_{n_y^2 \times n_u^2(2n-2m+2)} \\ \mathbf{G}_{2,1} & \cdots & \cdots & \mathbf{G}_{2,2n+1} \\ \mathbf{G}_{3,1} & \cdots & \mathbf{G}_{3,m+n} & 0_{n_u n_y \times n_u^2(n-m+1)} \\ \mathbf{G}_{4,1} & \cdots & \mathbf{G}_{4,m+n} & 0_{n_u n_y \times n_u^2(n-m+1)} \end{bmatrix}, \tag{79}$$

with $\mathbf{v}_{\mathbf{R}}(\tau) \in \mathbb{R}^{(n_y^2+n_u^2+2n_y n_u)\times 1}$, $\mathbf{v}_{\mathbf{R}_{z0}}(\tau) \in \mathbb{R}^{(2n+1)n_u^2\times 1}$, $\mathbf{G}(\boldsymbol{\theta}) \in \mathbb{R}^{(n_y^2+n_u^2+2n_y n_u)\times(2n+1)n_u^2}$, and 0 being null matrix of specified dimension, where

$$\{\mathbf{G}_{1,k}\}_{k=1}^{2m-1} = \left\{ \sum_{i=1}^{m}\sum_{j=1}^{m}(-1)^{m-j}\left(\mathbf{B}_j \otimes \mathbf{B}_i\right), \quad \forall \quad i+j = 2m+1-k \right\}_{k=1}^{2m-1}, \tag{80}$$

$$\{\mathbf{G}_{2,k}\}_{k=1}^{2n+1} = \left\{ \sum_{i=0}^{n}\sum_{j=0}^{n}(-1)^{n-j}\left(\mathbf{A}_j \otimes \mathbf{A}_i\right), \quad \forall \quad i+j = 2n+1-k \right\}_{k=1}^{2n+1}, \tag{81}$$

$$\{\mathbf{G}_{3,k}\}_{k=1}^{m+n} = \left\{ \sum_{i=1}^{m}\sum_{j=0}^{n}(-1)^{n-j}\left(\mathbf{A}_j \otimes \mathbf{B}_i\right), \quad \forall \quad i+j = m+n+1-k \right\}_{k=1}^{m+n}, \tag{82}$$

$$\{\mathbf{G}_{4,k}\}_{k=1}^{m+n} = \left\{ \sum_{i=0}^{n}\sum_{j=1}^{m}(-1)^{m-j}\left(\mathbf{B}_j \otimes \mathbf{A}_i\right), \quad \forall \quad i+j = m+n+1-k \right\}_{k=1}^{m+n}. \tag{83}$$

The system of equations in (76) contains $n_u^2 n + n_u n_y m$ unknowns in $\boldsymbol{\theta}$, $(2n+1)n_u^2$ unknowns in $\mathbf{v}_{\mathbf{R}_{z0}}(\tau)$, and $n_y^2+n_u^2+2n_y n_u$ equations. Since the number of equations must be at least as large as the number of unknowns, the condition

$$3nn_u^2 + (m-2)n_y n_u - n_y^2 \leqslant 0 \tag{84}$$

must be fulfilled. With the exception of very few cases, the system of equations in (76) is underdetermined. Two known exceptions are $n_u = 1, n_y = 2, n = 1, m = 1$ and $n_u = 1, n_y = 2, n = 2, m = 1$. Just as in [112], the system of equations (76) is made overdetermined by first considering derivatives of both sides, and then by considering these extended equations for several different lags. The description of the estimator is given as

$$\{\hat{\boldsymbol{\theta}}, \hat{\Lambda}\} = \arg\min_{\boldsymbol{\theta},\Lambda} J(\boldsymbol{\theta}, \Lambda), \tag{85}$$

$$J(\boldsymbol{\theta}, \Lambda) = \|\hat{\Gamma}(\boldsymbol{\theta}, \mathbf{s}, \tau) - \mathbf{G}(\boldsymbol{\theta}, \mathbf{s}, \tau)\Lambda(\boldsymbol{\theta}, \mathbf{s}, \tau)\|_{\mathbf{Q}}^2 \tag{86}$$

where $\hat{\Gamma}(\boldsymbol{\theta}, \mathrm{s}, \tau)$ is an estimate of (3.36) and $\mathbf{Q}$ is a symmetric and positive definite weighting matrix. Some properties of the proposed method are illustrated numerically.

B - Accuracy of errors-in-variables identification

This contribution is on the accuracy of a covariance matching method for continuous-time errors-in-variables identification. The purpose of the manuscript is to perform an accuracy analysis of a covariance matching method presented to solve the continuous-time errors-in-variables system identification problem. The continuous-time errors-in-variables system identification problem is described for the single input and the single output case. The assumptions needed for the covariance matching method and its analysis is presented. Just as in [104], the continuous-time errors-in-variables system identification problem is formulated as a nonlinear least squares problems with auxiliary unknowns as

$$\{\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\zeta}}\} = \arg\min_{\boldsymbol{\theta},\boldsymbol{\zeta}} \| \hat{\mathbf{r}} - \mathbf{F}(\boldsymbol{\theta})\boldsymbol{\zeta} \|_{\mathbf{Q}}^2, \tag{87}$$

where $\hat{\mathbf{r}}$ is a vector of covariances formed from the data and is an estimate of the true quantity $\mathbf{r}_0$, $\mathbf{F}(\boldsymbol{\theta})$ is a matrix whose elements are quadratic in the elements of the vector $\boldsymbol{\theta}$, $\boldsymbol{\zeta}$ is a vector of auxiliary parameter, $\mathbf{Q}$ is a positive definite weighting matrix, and $\hat{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\zeta}}$ are the respective estimates of the true quantities $\boldsymbol{\theta}_0$ and $\boldsymbol{\zeta}_0$. The analysis involves the evaluation of the asymptotic normalized covariance matrix, valid for a large number of data and a small sampling interval.

The asymptotic normalized covariance matrix $\mathbf{C}$ of the estimate $\hat{\boldsymbol{\theta}}$ in (87) is given as

$$\begin{aligned} \mathbf{C} &= \lim_{N\to\infty} N\mathrm{cov}(\hat{\boldsymbol{\theta}}) \\ &= \left(\mathbf{S}^T\mathbf{P}\mathbf{S}\right)^{-1}\mathbf{S}^T\mathbf{P}\mathbf{R}(h)\mathbf{P}\mathbf{S}\left(\mathbf{S}^T\mathbf{P}\mathbf{S}\right)^{-1}, \end{aligned} \tag{88}$$

where

$$\begin{aligned} \mathbf{R}(h) &= \lim_{N\to\infty} N\mathrm{cov}(\hat{\mathbf{r}}) \\ &= \lim_{N\to\infty} N\mathsf{E}\{(\hat{\mathbf{r}} - \mathbf{r}_0)(\hat{\mathbf{r}} - \mathbf{r}_0)^T\}, \end{aligned} \tag{89}$$

$$\mathbf{P} = \mathbf{Q} - \mathbf{Q}\mathbf{F}\left(\mathbf{F}^T\mathbf{Q}\mathbf{F}\right)^{-1}\mathbf{F}^T\mathbf{Q}, \tag{90}$$

$$\begin{aligned} \mathbf{S} &= \begin{bmatrix}\mathbf{s}_1 & \dots & \mathbf{s}_{n+m}\end{bmatrix}, \\ \mathbf{s}_j &= \mathbf{F}_j\boldsymbol{\zeta}_0, \\ \mathbf{F}_j &= \frac{\partial \mathbf{F}(\boldsymbol{\theta}_0)}{\partial \boldsymbol{\theta}_j}, \end{aligned}$$

with $\mathbf{F} = \mathbf{F}(\boldsymbol{\theta}_0)$ in (90).

Knowledge of the covariance matrix (88) not only makes it possible to assess the quality of the estimated parameter vector for a certain case, but also to study the effect of the user-chosen parameters of the method. The computation $\mathbf{R}(h)$ in (89) is the most difficult task for which following result is used.

$$
\begin{aligned}
G = \lim_{N\to\infty} N\mathsf{E}\Bigg\{ & \left(\frac{1}{N}\sum_t x_1(t)x_2(t) - r_{x_1^0 x_2^0}\right) \\
& \times \left(\frac{1}{N}\sum_s x_3(s)x_4(s) - r_{x_3^0 x_4^0}\right)\Bigg\}, \\
= & \sum_{\tau=-\infty}^{\infty} \{ r_{x_1x_3}(\tau) r_{x_2x_4}(\tau) + r_{x_1x_4}(\tau) r_{x_2x_3}(\tau) \},
\end{aligned} \tag{91}
$$

where

$$
x_j(t) = x_j^0(t) + \tilde{x}_j(t),
$$

for $j = 1, \ldots, 4$, with $\tilde{x}_j(t)$ being independent discrete-time white noise.

The approximate covariance matrix for large N and small h is given as

$$
\operatorname{cov}(\hat{\mathbf{r}}) \approx \frac{1}{Nh}\boldsymbol{T} \approx \frac{1}{Nh}\mathbf{M} + \frac{1}{N}\boldsymbol{\Gamma},
$$

where

$$
\boldsymbol{T} = \begin{pmatrix} \boldsymbol{T}_{00} & \ldots & \boldsymbol{T}_{0S} \\ \vdots & & \vdots \\ \boldsymbol{T}_{S0} & \ldots & \boldsymbol{T}_{SS} \end{pmatrix}, \tag{92}
$$

$$
\mathbf{M} = \begin{pmatrix} \mathbf{M}_{00} & \ldots & \mathbf{M}_{0S} \\ \vdots & & \vdots \\ \mathbf{M}_{S0} & \ldots & \mathbf{M}_{SS} \end{pmatrix} = \lim_{h\to 0} \lim_{N\to\infty} hN \operatorname{cov}(\hat{\mathbf{r}}), \tag{93}
$$

$$
\boldsymbol{\Gamma} = \begin{pmatrix} \boldsymbol{\Gamma}_{00} & \ldots & \boldsymbol{\Gamma}_{0S} \\ \vdots & & \vdots \\ \boldsymbol{\Gamma}_{S0} & \ldots & \boldsymbol{\Gamma}_{SS} \end{pmatrix}. \tag{94}
$$

The description of the resulting expressions $\mathbf{M}$ is derived and an example for the elements $(\mathbf{M}_{\mu\nu})_{11}$ given as

$$
\begin{aligned}
(\mathbf{M}_{\mu\nu})_{11} \quad = \quad & \mathsf{E}\left\{\left(p^{\nu} G^2 H^2 e_0(t)\right)\left(p^{\mu} G^2 H^2 e_0(t)\right)\right\} \\
+ \quad & \mathsf{E}\left\{\left(G^2 H^2 e_0(t)\right)\left(p^{\mu+\nu} G^2 H^2 e_0(t)\right)\right\}
\end{aligned}
$$

Similarly, a general expression for the $k\ell$-element of $\mathbf{\Gamma}_{\mu\nu}$ derived, which is expressed as

$$(\mathbf{\Gamma}_{\mu\nu})_{k\ell} = h \sum_{i=-\infty}^{\infty} \sum_{\varsigma=1}^{6} \gamma_\varsigma(i) \tag{95}$$

for $k, \ell = 1, \ldots, 4$, where

$$\begin{aligned}
\gamma_1(i) &= r_{p^\mu x_1^0, p^\nu x_3^0}(ih)\beta_2(i),\\
\gamma_2(i) &= r_{x_2^0, x_4^0}(ih)\beta_{1,\mu,\nu}(i),\\
\gamma_3(i) &= \beta_{1,\mu,\nu}\beta_2(i),\\
\gamma_4(i) &= r_{p^\mu x_1^0, x_4^0}\big((i+j)h\big)\beta_{4,\nu}(i),\\
\gamma_5(i) &= r_{x_2^0, p^\nu x_3^0}\big((i-j)h\big)\beta_{3,\mu}(i),\\
\gamma_6(i) &= \beta_{3,\mu}\beta_{4,\nu}(i),
\end{aligned}$$

and where

$$\begin{aligned}
\beta_{1,\mu,\nu}(i) &= \mathsf{E}\{p^\mu \tilde{x}_1(t+jh+ih)p^\nu \tilde{x}_3(t+jh)\}, &(96)\\
\beta_2(i) &= \mathsf{E}\{\tilde{x}_2(t+ih)\tilde{x}_4(t)\}, &(97)\\
\beta_{3,\mu}(i) &= \mathsf{E}\{p^\mu \tilde{x}_1(t+jh+ih)\tilde{x}_4(t)\}, &(98)\\
\beta_{4,\nu}(i) &= \mathsf{E}\{\tilde{x}_2(t+ih)p^\nu \tilde{x}_3(t+jh)\}, &(99)
\end{aligned}$$

vi.iii Outline of Part IV

Wireless channel modeling

In this contribution the dynamics of a scattered electric field at a moving receiver for a wireless channel is described by stochastic differential equations. In radio mobile communication, the transmitter is fixed and the receiver is generally moving. The multi-path components are available at the receiver due to reflections from the environment. The signal received at the receiver is described by Jakes's model as

$$r(t) = Re\left\{\sum_{k=1}^{P} A_k e^{i(2\pi f_k t - 2\pi f_c \tau_k)} e^{i(2\pi f_c t)}\right\}, = Re\left\{\mathsf{E}(t)e^{i(2\pi f_c t)}\right\}, \tag{100}$$

where

$$\mathsf{E}(t) = \sum_{k=1}^{P} A_k e^{i(\omega_k t + \phi_k(t))}, \tag{101}$$

$r(t)$ is the received signal at a moving receiver, P is the number of paths, and f_c is the carrier frequency of the baseband signal. Moreover, τ_k, f_k, and A_k are the corresponding time-delay, the Doppler frequency, and the strength, respectively, for path k. The random phase offset or the random phase shift $-2\pi f_c \tau_k$ is associated with the delay through the multi-path reception and may be represented by $\phi_k(t)$. Furthermore, $\mathsf{E}(t)$ represents the scattered electric field for the multi-path fading wireless channel and ω_k is the Doppler frequency in radians. The received signal can be decomposed as

$$r(t) = Re[\mathsf{E}(t)e^{i(2\pi f_c(t))}] = \mathsf{E}_I(t)\cos(2\pi f_c t) - \mathsf{E}_Q(t)\sin(2\pi f_c t), \tag{102}$$

where $\mathsf{E}_I(t)$ and $\mathsf{E}_Q(t)$ are the in-phase and quadrature components described as

$$\mathsf{E}_I(t) = \sum_{k=1}^{P} \cos\left(\omega_k t + \phi_k(t)\right), \quad \mathsf{E}_Q(t) = \sum_{k=1}^{P} \sin\left(\omega_k t + \phi_k(t)\right). \tag{103}$$

Two situations for the Doppler shift are considered. The first situation is with a received signal with negligible variations in the received Doppler frequency. Just as in [123], due to the random nature of the phases in (101), the increment $d\phi_k(t)$ of the phase $\phi_k(t)$ is modeled as

$$d\phi_k(t) = \sqrt{C}dW_k(t), \tag{104}$$

where C is a constant and $dW_k(t)$ is the increment of the Wiener process $W_k(t)$. It is assumed that the Wiener processes $\{W_k(t)\}_{k=1}^{P}$ are independent.

Using Ito's formula [136, 137] for (101),

$$\begin{aligned} d\mathsf{E}\big(t, \mathbf{W}(t)\big) = &\left(\frac{\partial \mathsf{E}\big(t, \mathbf{W}(t)\big)}{\partial t} + \frac{1}{2}\sum_{k=1}^{P} \frac{\partial^2 \mathsf{E}\big(t, \mathbf{W}(t)\big)}{\partial W_k^2(t)} \right) dt \\ &+ \sum_{k=1}^{P} \frac{\partial \mathsf{E}\big(t, \mathbf{W}(t)\big)}{\partial W_k(t)} dW_k(t), \end{aligned} \tag{105}$$

and results from [123, Appendix C], the approximate model in terms of stochastic differential equations is found

$$d\mathsf{e}(t) \approx \left(i\bar{\omega} - \frac{C}{2}\right)\mathsf{e}(t)dt + \sqrt{C}\sigma d\Gamma(t), \tag{106}$$

by using an approximation of $\frac{\partial \mathsf{e}(t)}{\partial t} \approx i\bar{\omega}\mathsf{e}(t)$.

The second situation is with a received signal with large variations in the received Doppler frequency. Multiple non-stationary objects in the path of the wireless channel explain this situation well, where each moving object incorporates its Doppler. A

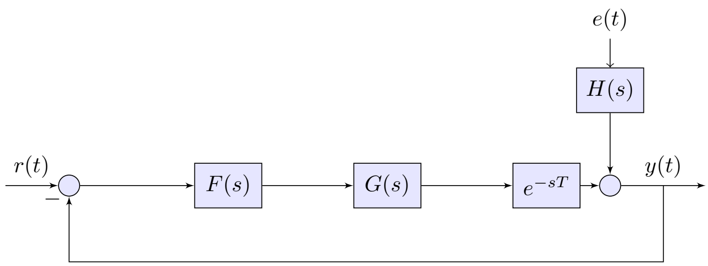

Figure 9: The closed-loop system configuration.

model for the random nature of the Doppler phase shift $\Phi_k(t)$ is proposed as

$$d\Phi_k(t) = \omega dt + d\varphi_k t, \tag{107}$$

where $\omega = 2\pi f$ is constant and $d\varphi_k(t) = \sqrt{D}dB_k(t)$, with $B_k(t)$ a Wiener process. This gives a modified Jakes's model. The Ito's formula is used as an intermediate step for the derivation of stochastic differential equation and the final description is given as

$$d\xi(t) = \left(i\omega - \frac{(C+D)}{2}\right)\xi(t)dt + \sqrt{C}\sigma d\Gamma_1(t) + \sqrt{D}\sigma d\Gamma_2(t), \tag{108}$$

with $d\Gamma_1(t)$ and $d\Gamma_2(t)$ being complex valued Wiener processes. The stochastic differential equation, whose parameters can be interpreted physically, facilitates efficient simulations as only one complex valued signals for the first situation, and two complex valued signals for the the second situation (108) are required. A comparison between the derived stochastic differential equations and the Jakes's model describing the scattered electric field is made, which is based on the comparison of the second order statistical properties.

vi.iv Outline of Part V

Closed-loop identification

The contribution deals with estimation of the parameters of a system in a closed-loop from irregularly sampled data, which is described in Figure 9. The model of the system in closed-loop is described by $G(p) = B(p)/A(p)$, which is controlled by $F(p) = \frac{F_1(p)}{F_2(p)}$, a proportional (P) or a proportional integral (PI) controller where the controller parameters are assumed known. The closed-loop contains a time-delay, approximated as $e^{-sT} \approx \Delta(s) = \frac{\Delta_1(s)}{\Delta_2(s)}$, where $\Delta(s)$ is a rational transfer function.

The closed-loop system is described by a continuous-time ARMAX process

$$y(t) = G_{ry}(p)r(t) + G_{ey}(p)e(t), \tag{109}$$

where $r(t)$ is the reference signal and

$$G_{ry}(p) = \frac{\Delta_1(p)B(p)F_1(p)}{\Delta_2(p)A(p)F_2(p) + \Delta_1(p)B(p)F_1(p)}, \tag{110}$$

$$G_{ey}(p) = \frac{\Delta_2(p)F_2(p)}{\Delta_2(p)A(p)F_2(p) + \Delta_1(p)B(p)F_1(p)}, \tag{111}$$

whose parameters are difficult to estimate due to the structure of $G_{ey}(p)$. However, by introducing a filtration approach, (109) can be written as

$$\bar{y}(t) = G_{ry}(p)\bar{r}(t) + \bar{G}_{ey}(p)e(t), \tag{112}$$

where $\bar{y}(t) = (1/\Delta_2(p)F_2(p))y(t)$, $\bar{r}(t) = (1/\Delta_2(p)F_2(p))r(t)$, and

$$\bar{G}_{ey}(p) = \frac{1}{\Delta_2(p)A(p)F_2(p) + \Delta_1(p)B(p)F_1(p)}. \tag{113}$$

Moreover, let $G_{ry}(p) = \bar{B}(p)/\bar{A}(p)$, and $\bar{G}_{ey}(p) = 1/\bar{A}(p)$, where $\bar{A}(p) = p^m + \alpha_1 p^{m-1} + \ldots + \alpha_m$, $\bar{B}(p) = \beta_1 p^{m-1} + \ldots + \beta_m$, and express (112) as

$$\bar{A}(p)\bar{y}(t) = \bar{B}(p)\bar{r}(t) + e(t). \tag{114}$$

This means that (114) can be written in the linear regression form as

$$\rho(t_k) = \boldsymbol{\varphi}^T(t_k)\boldsymbol{\psi} + \epsilon(t_k), \tag{115}$$

with $\epsilon(t_k)$ being an equation error. The parameters $\boldsymbol{\theta}_0 = [a_1, \cdots, a_n, b_1, \cdots, b_m]^T$ can now be estimated using the approach in [138, 139]. Finally, a mapping of the estimate $\hat{\boldsymbol{\psi}}$ onto estimates $\hat{\boldsymbol{\theta}}$ and $\hat{T}$ must be made.

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On some continuous-time modeling and estimation problems for control and communication

The scope of the thesis is to estimate the parameters of continuous-time models used within control and communication from sampled data with high accuracy and in a computationally efficient way. In the thesis, continuous-time models of systems controlled in a networked environment, errors-in-variables systems, stochastic closed-loop systems, and wireless channels are considered. The parameters of a transfer function based model for the process in a networked control system are estimated by a covariance function based approach relying upon the second order statistical properties of input and output signals. Some other approaches for estimating the parameters of continuous-time models for processes in networked environments are also considered. The multiple input multiple output errors-in-variables problem is solved by means of a covariance matching algorithm. An analysis of a covariance matching method for single input single output errors-in-variables system identification is also presented. The parameters of continuous-time autoregressive exogenous models are estimated from closed-loop filtered data, where the controllers in the closed-loop are of proportional and proportional integral type, and where the closed-loop also contains a time-delay. A stochastic differential equation is derived for Jakes's wireless channel model, describing the dynamics of a scattered electric field with the moving receiver incorporating a Doppler shift.

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